AQUA
Water Infrastructure, Ecosystems and Society

 AQUA — Water Infrastructure, Ecosystems and Society Vol 73 No 3, 688 doi: 10.2166/aqua.2024.038

Construction of community health care integration using artificial intelligence models

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ABSTRACT

In the information age, there's a growing need to improve eldercare services for the mobile elderly population. Current Chinese eldercare often separates medical and nursing care, leading to low resource use. This study aims to integrate community healthcare with data analysis and intelligent coordination to meet the floating elderly's needs. Using a Stacking model, it identifies key indicators and develops a mobile terminal based community healthcare model. Results show that primary indicators are crucial, scoring between 4.48–5.00, with secondary and tertiary indicators also significant. The KMO value is 0.93, confirming the model's validity. Compared to traditional methods, this new approach enhances accuracy by 7%, offering a valuable framework for community-based eldercare integration in China.

Key words: data mining and intelligent coordination, elderly mobile population, pollution, public health, strategy optimization

HIGHLIGHTS

- This research mainly focuses on the integration model of the elderly floating population and community health care.
- The experimental results showed that the model proposed the importance of community health care indicators for the elderly floating population, with a distribution of 4.48–5.00 and a full score of 52.17–100%.

1. INTRODUCTION

The level of medical care is improving, and the life expectancy in China is increasing, but at the same time, the new lifestyle and new family model make the fertility rate is also decreasing, which will lead to the imbalance of China's population structure and the aging of the population is becoming more and more serious. The 2017 Social Services Development Statistics Bulletin (Abir *et al.* 2020) shows that by the end of 2017, China will have 35% of its population over the age of 60 years, making it the most severely aging country in the world (Chen 2019). When China entered the aging society, it was not yet modernized, its economy was underdeveloped, and it had the demographic characteristic of 'aging before getting rich' (Alemdar & Ersoy 2010). The dependency ratio of China's elderly population shows a trend of increasing year by year, as shown in Table 1.

In today's growing elderly population and elderly mobile population, the traditional elderly care model is single, and the lack of medical functions and resources in traditional elderly care institutions, and in the process of long-term care and nursing care, care and medical care are closely related, and many disabled elderly people need more comprehensive care in long-term care combined with medical resources (Yuehong *et al.* 2016; Guo *et al.* 2019). Single traditional elderly care institutions cannot meet the long-term 'medical + nursing' needs of the elderly in a comprehensive manner. This problem can be solved by community-based 'medical + nursing' elderly care services, which are government-led, community-based. Community-based 'combined medical and health care' elderly care services are an important solution to the problem of socialized elderly care in the context of the increasing population aging in China, and a new way to alleviate the current unreasonable allocation of social elderly and medical resources (Chan *et al.* 2012).

Community health care integration is to take the community as a platform to fully combine the elderly resources with medical resources, and improve the effectiveness of the combination of elderly and medical resources, which can ensure that the

Table 1 | Age structure and dependency ratio of elderly mobile population

		65 years old and above			
Particular year	**Total population (year-end)**	**Population**	**Specific gravity (%)**	**Total dependency ratio (%)**	**Elderly dependency ratio (%)**
2008	132,129	10,956	8.3	37.4	11.3
2009	133,450	11,307	8.5	36.9	11.6
2010	134,019	11,894	8.9	34.5	11.9
2011	134,735	12,288	9.1	34.4	12.3
2012	135,404	12,714	9.7	35.3	13.1
2013	136,072	16,312	9.6	35.6	13.2
2014	136,782	13,755	10.1	36.2	13.9
2015	137,462	14,385	10.5	37.1	14.2
2016	138,271	15,003	10.9	37.8	15.2
2017	139,008	15,831	11.5	39.6	15.4

elderly can enjoy cultural activities, daily care and other elderly services through the community on the one hand, and also enable the elderly to directly enjoy preventive health care, rehabilitation treatment and other medical On the other hand, it also enables the elderly to enjoy medical services such as preventive health care and rehabilitation treatment directly in the community (Górriz *et al.* 2020). Compared with the traditional community elderly care model, the most prominent feature of the community 'combined medical care' elderly care service model is that it can provide not only simple preventive medical services for the elderly but also specialized medical services such as health examination, emergency treatment, rehabilitation care and disease treatment for the elderly. The proportion of the community elderly service model is about 6%, and the proportion of the institutional elderly care model is about 4% of all elderly care models (Islam *et al.* 2015).

Under the vision of artificial intelligence, the community health care information service system uses big data, Internet, and other information technologies to provide intelligent health elderly services in institutions, mainly by providing the elderly with regular and real-time monitoring of physical health data, mobile positioning, alerts of abnormal conditions, and physical health data management (Bardhan *et al.* 2020). It realizes the information transmission and interaction between the elderly and the elderly institutions, medical caregivers, and children, and provides effective monitoring of the daily activities and health conditions of the elderly in the elderly institutions, as well as provides the elderly with other needs in life and entertainment, and improves the elderly services in the elderly institutions. Traditional data analysis and data transmission methods have difficulties in data query, information sharing, inspection and supervision, paper storage, and data omission, which are unable to effectively analyze and process such a large and complicated data type to provide more help to the upper level (Fritz & Dermody 2019).

The full English name of the CART model is Classification and Regression Tree, and its corresponding Chinese interpretation is Classification Regression Tree. In general, this method is a classification data mining algorithm. It is a flexible way of describing the conditional distribution of the variable Y given the predictive vector value X. The model uses a binary tree to recursively divide the prediction space into subsets where Y is distributed continuously and uniformly. The leaf nodes in the tree correspond to different regions of the division, which is determined by the branch rules associated with each internal node. By moving from root to leaf node, a prediction sample is assigned a unique leaf node, and the conditional distribution of Y on that node is also determined. This method was proposed by Breman *et al.* There are significant differences between this method and the previous classification method ID3, which are mainly reflected in the following three aspects: the impure measure used to select variables in CART is the Gini index; If the target variable is nominal and has more than two classes, CART may consider merging the target class into two superclasses (bimorphization); If the target variable is continuous, the CART algorithm finds a set of tree-based regression equations to predict the target variable. The core idea of the algorithm is binary recursion, through this binary way, the collection data originally classified in a big class is segmented. That is to say, a sample set is divided into two sample sets and four sample sets in turn. The specific progress of sample segmentation is determined by the specific attributes of the data. By this segmentation, there are two branches in every node of non-leaf node. There are 4 different levels of impurity that can be used to find the partitioning of CART models, depending on the type of target variable, for the target variable of classification, you can choose GINI, bibialization or ordered bialization; For continuous target variables, the least square deviation (LSD) or the least absolute deviation (LAD) can be used. The core of the CART algorithm to maintain efficiency is to ensure that every non-leaf node exists with the maximum probability, which is enough to say, that for the leaf nodes with low or extremely low probability, pruning operations must be carried out to ensure the execution efficiency of CART tree.

In a word, although the informatization of community medical integration is still in its infancy, the current situation of elderly care services can be improved by using advanced information technology, effectively integrating social elderly care service resources and improving management efficiency. This will certainly bring new direction to the elderly care service in the future, and provide better and more efficient services for the united community health care.

With the promotion of artificial intelligence technology, the construction of community health integration has become a reality. With the gradual improvement of community medical information, we can foresee that community elderly care services will usher in a revolutionary change. Through the use of advanced information technology, the social elderly care service resources are effectively integrated to improve management efficiency and service quality, with the guidance of an artificial intelligence model, community health care integration is moving towards a more intelligent and efficient development direction. Through the application of intelligent AI technology and the Internet of Things, community medical care will further improve the quality of service and better meet the needs of residents for the elderly. At the same time, community health care also needs to achieve close cooperation with other related institutions to jointly promote the development of community health integration. It is believed that in the near future, the integration of community health care will bring more high-quality and efficient elderly care services for our elderly.

2. RELATED WORKS

The population structure of European society has undergone unprecedented changes – the population is rapidly aging. The aging problem has a direct impact on the social and economic development of Europe. In this context, foreign scholars have carried out research and have conducted more in-depth research and exploration on this topic.

First, in terms of community-based elderly care theory, the literature (Azzi *et al.* 2020) points out that the problem of medical reimbursement in medical and nursing care service institutions is not well solved, which restricts a series of problems brought about by reimbursement, and the lack of corresponding policy support brings about a lag in the development of the institutions. The literature (Gams *et al.* 2019) points out that from the perspective of the current long-term development of the floating elderly population, all relevant institutions lack systematicness and linkage, and the entire medical and elderly care system is not planned in a comprehensive way. The literature (Holroyd 2022) points out that the ratio of institutional beds to the number of elderly population in elderly care institutions does not meet the standard. There is still some distance from the national target. The development between urban and rural areas and between elderly institutions with different attributes has also not reached a balance. Some elderly institutions have too low occupancy rates due to poor environmental facilities, while others discourage the elderly due to inflated prices.

Second, in terms of medical services, in recent years, more and more elderly people in China have lost their self-care ability and become disabled, and the number of elderly people with full self-care ability is decreasing. The literature (Pramanik *et al.* 2017) argues that the combination of medical institutions and elderly institutions consists of three joint cooperation models between elderly institutions and medical institutions to achieve the organic combination of both. Literature (Batty *et al.* 2012; Skouby & Lynggaard 2014; Syed *et al.* 2019) pointed out that it is necessary to form a government-led force, social forces go hand in hand, and the whole society participates in a senior care service system that highlights the combination of medical care and nursing care. Literature (Zhou *et al.* 2022) proposed to establish a social insurance long-term care system, fund 'contracted doctors', change the payment structure of medical insurance, participate in medical insurance funds to raise combined services, etc., and reasonably design the coverage items and reimbursement scope.

Thirdly, in terms of combined community medical and nursing care services. In developed countries, due to the influence of economic and cultural factors, the population services under the combined medical and nursing model are also faster, and the United States first defined such elderly care services as 'long-term care system for the elderly' in 1963. In recent years, the literature (Cai *et al.* 2019) suggests that the integration of medical and elderly services can have a positive impact on society as a whole, optimizing the service experience of the elderly population while reducing costs and promoting the rational allocation and utilization of resources for the participating social organizations. According to the literature (Sakr & Elgammal

2016), the elderly care services under the integrated medical care model should cover 'nursing care, non-technical care and professional medical care', and should meet the special. A study in the literature (Roberts *et al.* 2021) found that older age groups generally prefer to receive services without being away from their families or communities of origin and that they would feel more secure, identified, and autonomous as a result. In terms of service provision, the literature (Li *et al.* 2015) argues that, in addition to the support of family members, the power of social organizations should not be neglected in the long-term aging process of the elderly, and that by working together to maximize the value of the community, they are committed.

In fact, the literature (Acampora *et al.* 2013; Ng 2018) generally argues that the special national situation of population aging and the changing needs of elderly groups in China for elderly care make the establishment of a combined medical and nursing care service model inevitable. Second, consumption upgrading, as a product of economic and technological development, represents that users' consumption behaviors and concepts are changing. This is also true for the elderly market, where people's demand for elderly care is no longer limited to material life, and it is imperative to expand the value space of elderly care services. Accordingly, the literature (Doukas *et al.* 2011) points out that the spiritual needs of the elderly and the pursuit of health and quality of life are growing, and the traditional elderly service model. In terms of resource allocation and utilization, literature (Doukas *et al.* 2011) also pointed out that medical and elderly services have long been two relatively independent service modules, for example, elderly people are hospitalized for a long time due to chronic diseases, which causes a waste of resources for the hospitals providing the services, and the combined medical and elderly care model can effectively solve this problem of unbalanced resource allocation.

In summary, the integration of the elderly mobile population based on data analysis and intelligent coordination in the context of artificial intelligence has a wide social value and theoretical foundation.

Through the application of artificial intelligence, a community health integration model can be built to provide comprehensive health management and care services for the elderly floating population. In the context of artificial intelligence, the use of data analysis and intelligent coordination can better solve the social problems faced by the elderly floating population.

To sum up, using data analysis and intelligent coordination under the background of artificial intelligence to build a community health care integration model has broad social value and theoretical basis for the elderly floating population. Through the use of artificial intelligence technology, comprehensive health management and care services for the elderly floating population can be achieved, and their quality of life and happiness can be improved. At the same time, it also provides new directions and opportunities for community building and social development. In the future, we look forward to the AI model further playing a role in the integration of community health care to create a healthier and better life for the elderly migrant population.

3. A MACHINE MATHEMATICAL MODEL OF COMMUNITY-BASED HEALTH CARE INTEGRATION FOR THE ELDERLY MOBILE POPULATION

As early as 2012 people paid attention to and evaluated the operability and safety of IoT technology in medical elderly services, the information collected through IoT technology has been applied to data analysis on a large scale.

In the construction of the mathematical model of community health care integration for the elderly mobile population, the decision tree algorithm classifies according to the optimal features, and the split features are selected by using the information gain method, and those with large gain values are preferred, but in the classification process, it is easy to have too many feature values leading to too large information gain values, which makes the classification efficiency and accuracy seriously decreased.

In the specific application of the CART decision tree algorithm in the calculation of health care integration of the elderly mobile population in this community, the Gini index is used to represent the probability of a random sample being misclassified, taking a value in the range of (0–1), assuming that the data set needs to be classified into K categories and the sample data is classified into the Kth probability of pk. Thus the Gini index can be defined as Equation (1):

$$Gini(\mathrm{p}) = \sum_{k=1}^{k} p_k(1 - p_k) = 1 - \sum_{k=1}^{k} p_k^2 \tag{1}$$

Description: Variable p_k represents the prior probability of node data belonging to class k; Variable. The variable n represents the total number of classes; The variable GINI stands for the Gini coefficient. GINI is the impurity function $E(t)$.

Since the CART decision tree is a dichotomous decision tree in the mathematical model of community health care integration for the elderly mobile population, the decision tree will be partitioned into D_1, D_2, and the Gini index of the set D under the condition of the feature A, which is defined in Equation (2).

$$Gini(\mathrm{D, A}) = \frac{D_1}{D} Gini(D_1) + \frac{D_2}{D} Gini(D_2) \tag{2}$$

Under the condition that the data are linearly divisible, assume that there exist i training sets $\{(x_i, y_i), i = 1, 2, 3 \ldots l\}$, with an expected output value $y_i \in \{+1, -1\}$, where -1 and $+1$ represent the category identifiers of two classes of samples, each located on one side of the hyperplane. The hyperplane is denoted as: $W^T x_i + b = 0$. Assuming that d is the distance from the nearest observation to the hyperplane, in order to make the hyperplane classify all samples reasonably and keep a certain distance, the classification condition is constructed as shown in Equation (3) for the ith observation of the community health care integration model.

$$\left.\begin{array}{ll} W^T x_i + b \geq d & y_i = +1 \\ W^T x_i + b \leq -d & y_i = -1 \end{array}\right\} \Leftrightarrow y_i(W^T x_i + b) - d \geq 0 \tag{3}$$

To make the fit of the health care integration model for the community elderly population achieve the most ideal classification, the simplified interval Equation (4) is:

$$y_i(W^T x_i + b) \geq 1 \tag{4}$$

As shown in Equation (4), if the output variable $y_i = +1$, then $W^T x_i + b \geq 1$; if $y_i = -1$, then $W^T x_i + b \leq -1$. The idea of the support vector machine algorithm is maximized when the value of $2d$ is maximized $\|W\|$, and the value of can be minimized when the value of $2d$ is maximized. Therefore, in the linearly differentiable case, the SVM optimization model with constraints is shown by Equations (5) and (6):

$$\begin{cases} \min \tau(W) = \min \frac{1}{2}\|W\|^2 = \min \frac{1}{2} W^T W \\ \text{st.} \quad y_i(b + W^T x_i) - 1 \geq 0, i = 1, 2, \cdots m \end{cases} \tag{5}$$

$$L(W, b, \lambda) = \frac{1}{2}\|W\|^2 - \sum_{i=1}^{m} \lambda_i (y_i(b + W^T x_i) - 1) \tag{6}$$

Then, the simplified hyperplane of the mathematical model of health care integration for the elderly mobile population in the community can be obtained from the optimal classification function as shown in Figure 1, and the vectors A, B and C are parallel to the optimal hyperplane and therefore are the support vectors satisfying the constraint equal sign.

In fact, the kernel function needs to be introduced when using support vector machines to classify linearly indistinguishable sample data, and converting the linearly indistinguishable problem into a linearly divisible problem. To accommodate linearly indistinguishable samples, the relaxation variables ε_i need to be introduced to the hyperplane $w\phi(x) + b = 0$ after mapping ϕ transformation, and the introduction of the relaxation variables ε_i inequality is shown in Equation (7):

$$\left.\begin{array}{lll} wx_i + b \geq 1 - \varepsilon_i & \text{for} & y_i = +1 \\ wx_i + b \leq -1 + \varepsilon_i & \text{for} & y_i = -1 \end{array}\right\} \Leftrightarrow y_i(wx_i + b) + \varepsilon_i \geq 1 \tag{7}$$

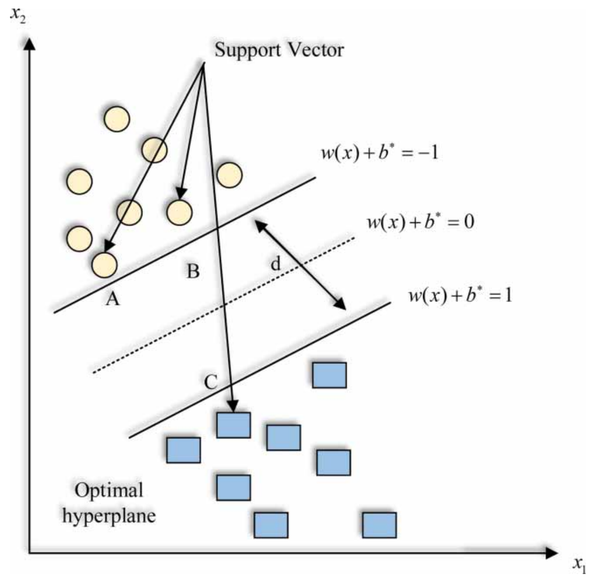

Figure 1 | Simplified hyperplane of the mathematical model of health care integration for the elderly mobile population in the community.

It follows that the optimal classification function of the mathematical model of health care integration for the elderly mobile population in the community, see Equation (8):

$$f(x) = \mathrm{sgn}\left\{\sum_{i=1}^{l} y_i \lambda_i^* \phi(x)\phi(x_i) + b^*\right\} \tag{8}$$

4. METHODS

4.1. Model build and run

The disease management service for the elderly mobile population under the community health care integration model has gradually taken shape, forming a three-level linkage disease management service system among community hospitals, third-party enterprises and the streets where the community is located, with the three working together to serve the medical and health care life of elderly users. In the grey system, the external characteristics are semi-known and the relationship between the factors is not clear. Grey system is often applied to grey correlation analysis, grey prediction and grey decision making. Usually, when considering the degree of influence of one factor on another factor, if the sequence curve between the two factors tends to be similar, it indicates that the correlation degree between the two factors is high, whereas if the sequence curve between the two factors tends to be opposite, it indicates that the correlation degree between the two factors is low. Therefore, grey correlation analysis is used to measure the similarity or opposite degree of the changing trend between multiple factors, which is also said to be the 'grey correlation degree'. In the calculation of the grey correlation analysis method, the relationship between factors will be expressed by correlation degree. In the calculation of the reference sequence and comparison sequence, the curve similarity between each sequence will be analyzed, and the similarity will be finally obtained. If the distance between the series curves is close, the correlation is strong; otherwise, the correlation is low, as shown in Figure 2.

In this model, the community hospital is responsible for the daily diagnosis and communication of the elderly with nearby diseases, dispensing and tracking of their conditions, and carrying out corresponding health education. After contracting with the community, the third-party company invests in medical equipment and nursing staff/helpers in the community between the nursing staff/helpers and the elderly and connects with the community pharmacy to provide targeted medical and health services for the elderly, such as accompanying medical consultations, dispensing medication, and assisting in daily care. Although the third-party company and the community hospital are two institutions, they are combined with each other to interconnect the health data of the elderly. The feedback received by the caregivers/helpers is continuously replenished to

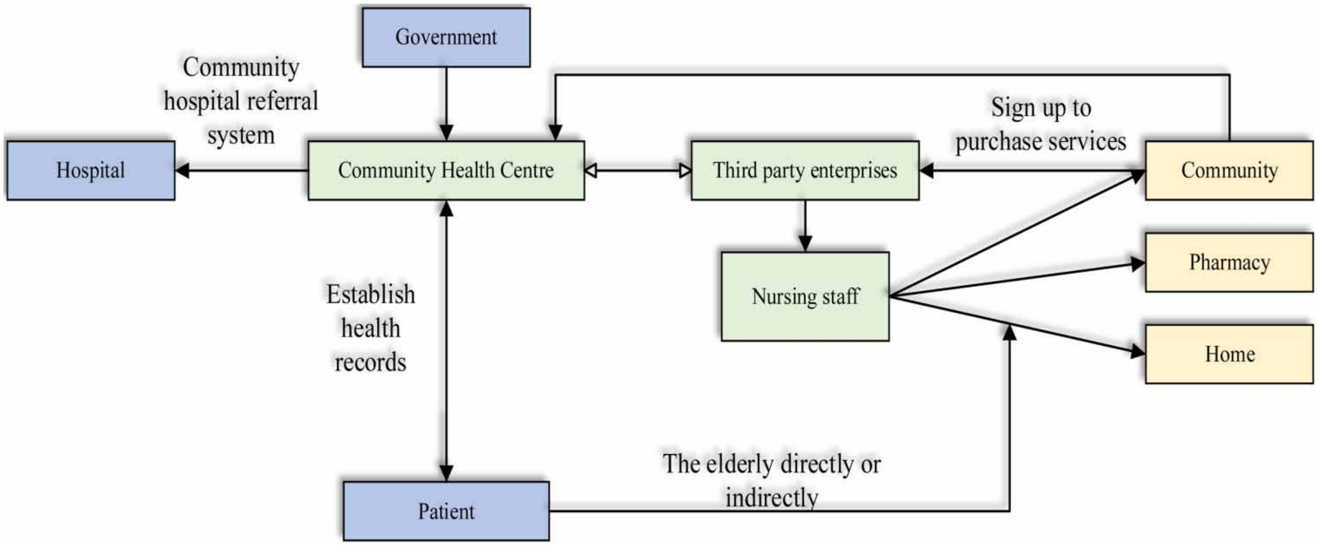

Figure 2 | Model of community health care integration service system for elderly mobile population.

the community hospital to assist the community hospital in the disease management of elderly patients. Therefore, in this paper, while collecting data through IoT devices, we also cooperate with official departments such as civil affairs departments and street offices to obtain health data of the elderly and design and organize the service content, while third-party service providers cooperate to jointly implement community elderly services and iteratively update the service content several times, where the third-party organizations mainly include: medical institutions, terminal equipment The third-party organizations include medical institutions, terminal equipment providers, home care providers, nutritional meal suppliers, etc. The cooperation model of integrated community elderly care services is shown in Figure 3.

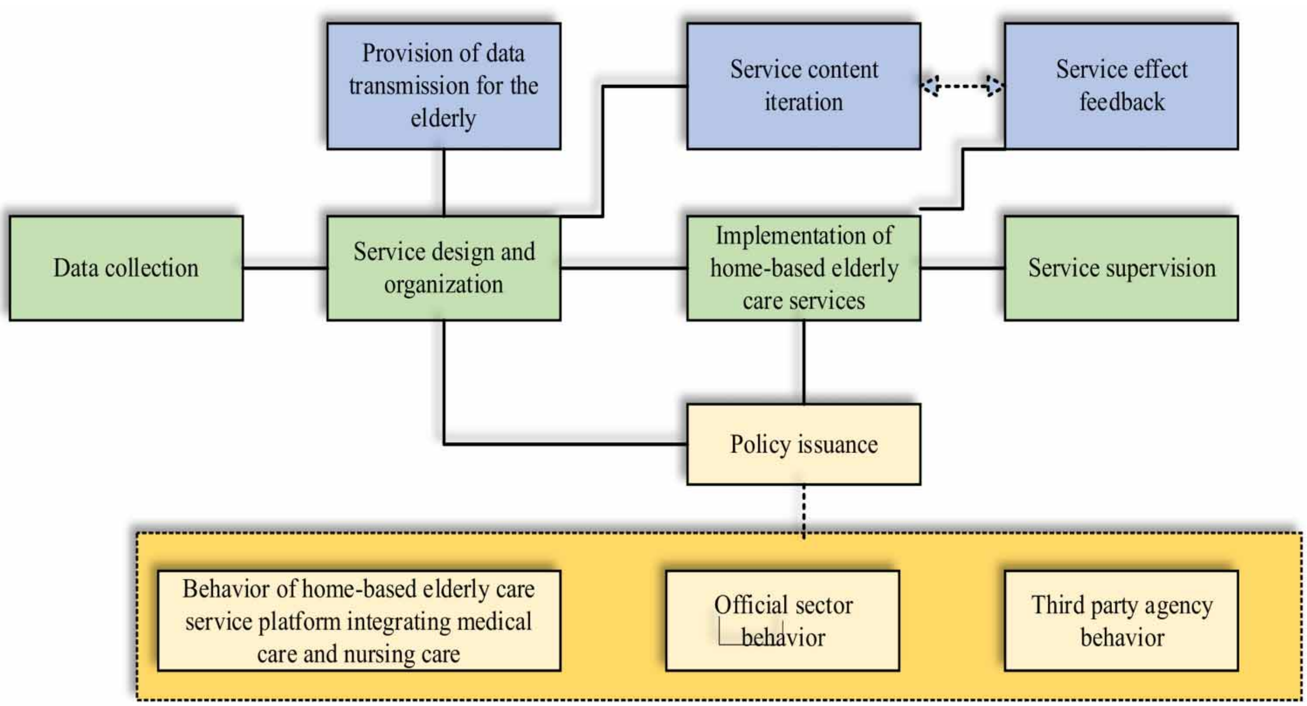

Figure 3 | Cooperation model of combined medical and health care community elderly service platform.

From the above analysis, it can be seen that the services of the elderly floating population should be kept more active, which is mainly due to the uncertain characteristics of the floating population. Therefore, this mathematical model also sets up an operation mode, as shown in Figure 4.

In this mode, the association of roles means the accuracy of the model. Therefore, after the role association relationship is sorted out, this paper combines the results of service role function analysis and the design principle of the use case diagram to visualize the service role association. The service role association diagram is shown in Figure 5.

In this model, there is also a certain service demand forecasting function for the elderly floating population, which means collecting and simulating the life data of this part of the elderly, as shown in Figures 6 and 7.

Then, based on the overall logic of the above design service and the specific implementation process, the community monitoring environment based on IoT technology is built by using appropriate smart terminal hardware to ensure the personal safety of community elders while laying the foundation for the subsequent implementation of intelligent functions and empirical analysis of the data set.

4.2. Data Set fetching and analysis

Based on the model we built in the previous section, we conducted database conversion and digital relationship measurement, and designed the database with E-R model to store physical data and analog data differently, as shown in Figure 8.

In addition, mining effective information from the collected data and using it is the key to realize intelligent services, in which data pre-processing is an important part of the data analysis process and an important basis to ensure scientific and accurate research prediction.

This paper refined the data provided by the China Geriatrics Center and obtained 2,311 valid sample data that meet the collection criteria of this paper, including 1,103 male data and 1,208 female data, with an average age of 63.2 years. In this paper, we use these data as samples to build and train the predictive model of typical cases of middle-aged and elderly

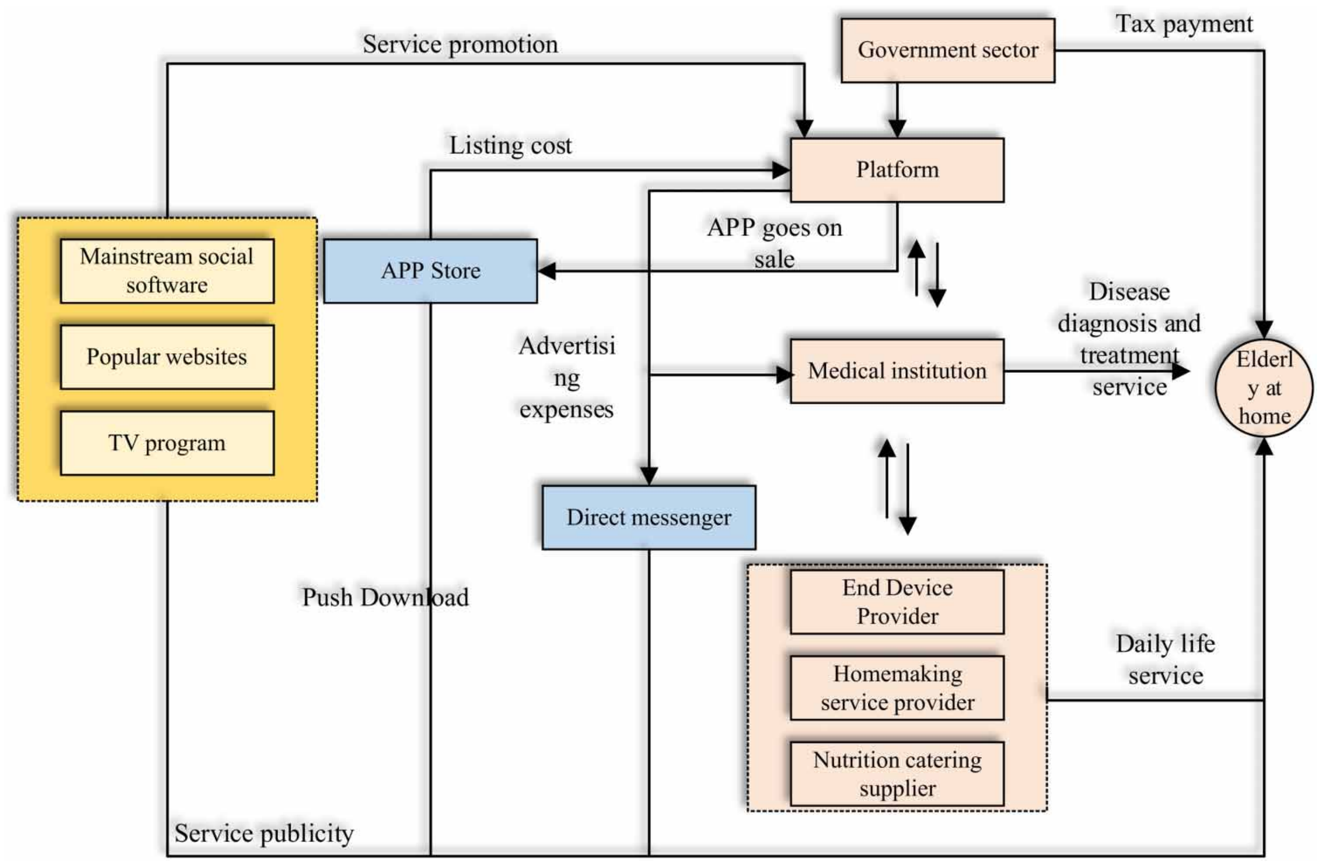

Figure 4 | Digital model business operation model of community health care integration for elderly mobile population.

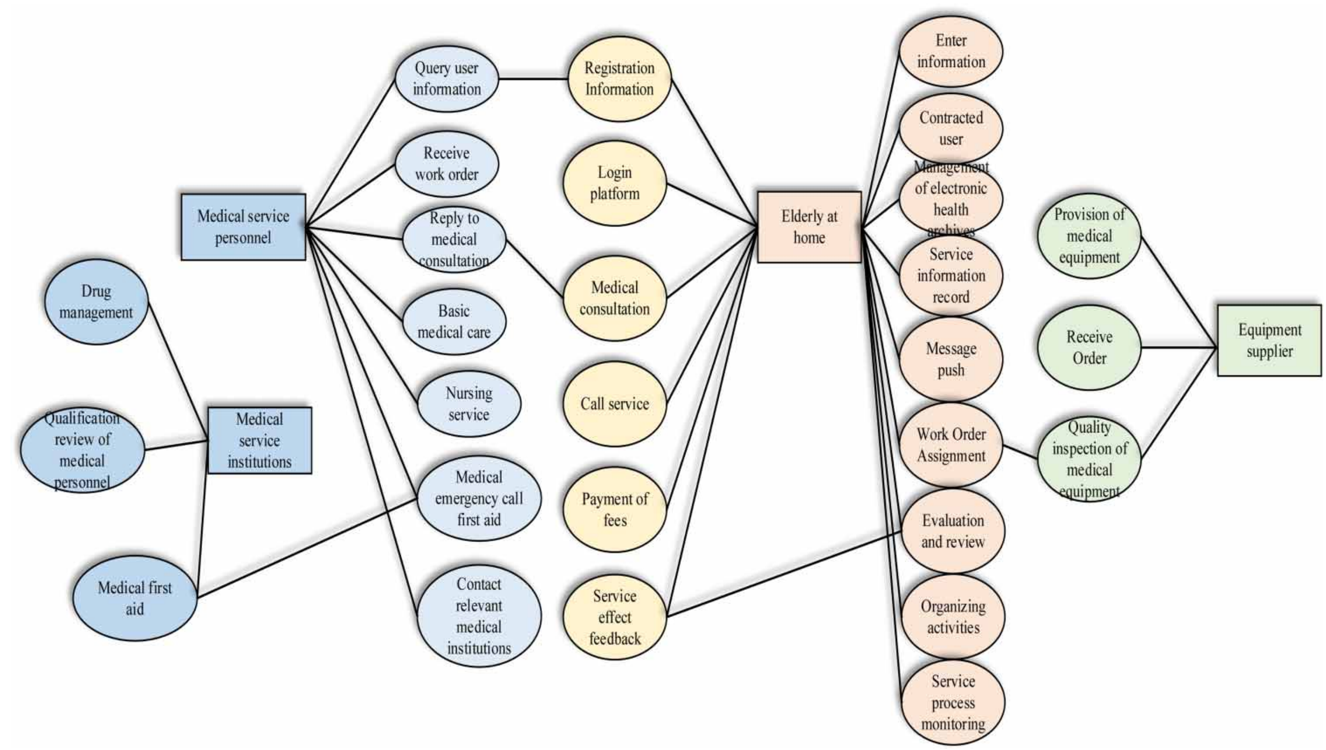

Figure 5 | Role association diagram of the digital model of community health care integration for the elderly mobile population.

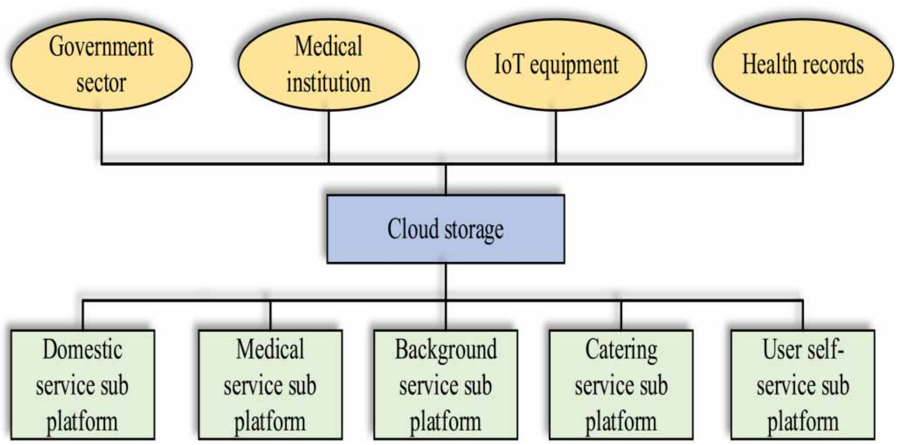

Figure 6 | Digital model data access pattern of community health care integration for elderly mobile population.

people in the floating population, such as heart disease. This model does not exclude the wider population, including the elderly in the community. There are blank values, incorrect data values, and inconsistent data formats in the original data set. Therefore, this paper processes data by removing null values, data conversion and data interpolation. The section data intercepted after preprocessing is shown in Table 2, and the feature meanings are shown in Table 3.

In order to improve the accuracy of the results, this paper uses the parameter value of the disease (target) as an indicator, and uses the Kano optimization model to summarize the correlation, so as to calculate the demand importance score of the elderly floating population. If the score is greater than 1, it means that the elderly floating population has a demand for disease care, and if it is 0, it means that the elderly floating population has a small demand for disease care.

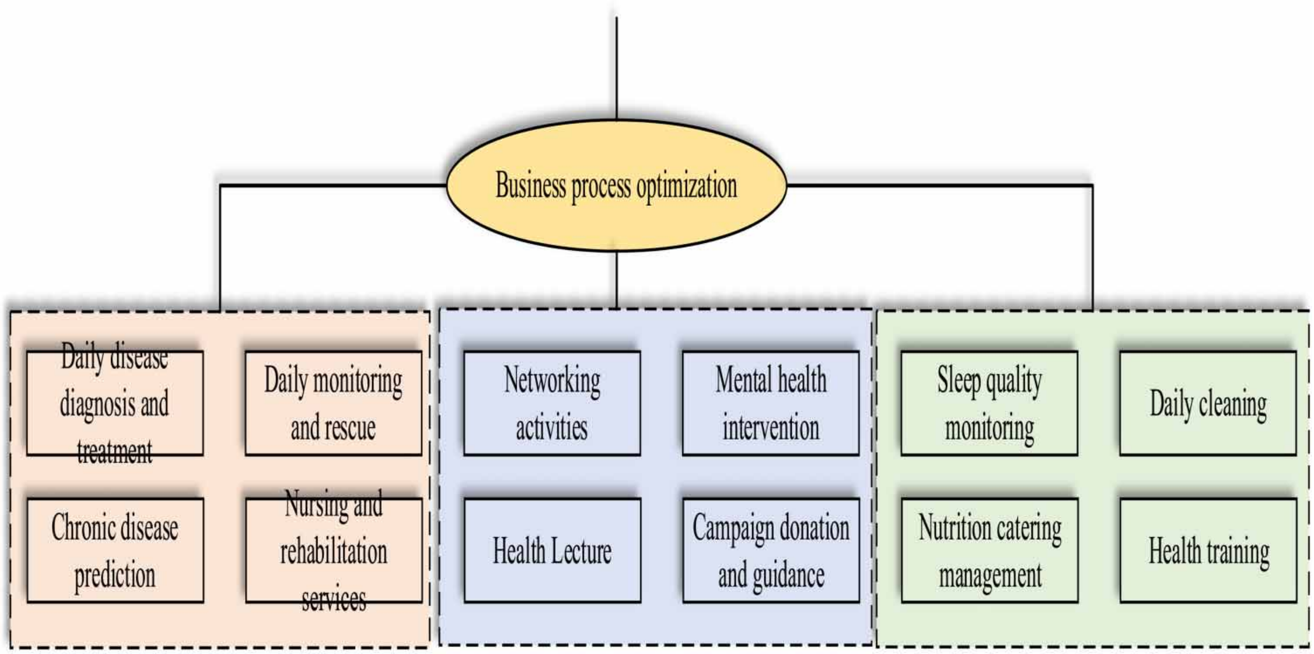

Figure 7 | Digital model business operation mode of community health care integration for elderly mobile population.

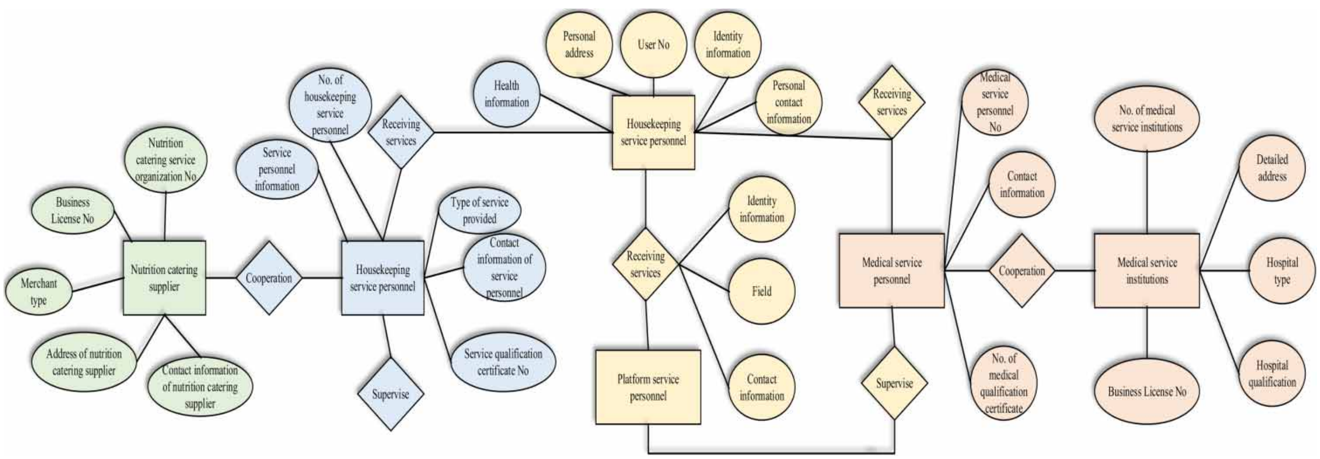

Figure 8 | E–R model of community health care integration database.

During the data processing, this paper used the prevalence of illness as the dependent variable and 13 indicators such as age, type of chest pain, resting blood pressure, plasma steroid level, fasting blood glucose, and maximum heart rate as independent variables, and used gray correlation analysis to describe the strength between influencing factors by the value of correlation coefficients to calculate the degree of influence of the dependent variable prevalence in order to further screen the effective The grey correlation analysis can be used to calculate the degree of influence of the dependent variable on the case data by the independent variable. The gray correlation analysis method can largely reduce the loss caused by information asymmetry and can compensate for the problem of small data samples and insignificant data regularity. After dimensionless analysis, the correlation coefficients between the comparison series and the reference series corresponding to the influencing factors are calculated, where ρ is the discrimination coefficient, $0 < \rho < 1$. The smaller value of P indicates that the correlation coefficients are more easily distinguished from each other. The process of calculating the correlation

Table 2 | Values for the community health care integration data set

Age	Gender	Types of chest pain	Resting blood pressure	Plasma steroid content	Fasting blood glucose	ECG	Maximum heart rate	ST decrease caused by movement	Slope of ECG ST at maximum exercise	Slope of ST	Number of main blood vessels measured by fluorescent staining	THAL value	Sickness
69	1	3	130	320	0	2	108	0	2.4	2	3	3	0
65	0	1	116	562	0	2	155	0	1.6	2	0	6	1
58	1	2	128	260	0	0	124	1	0.5	1	2	7	0
62	0	2	135	254	0	0	123	1	0.2	2	1	6	1
60	1	2	125	267	1	2	142	0	1.2	3	2	5	0
63	1	2	138	298	0	2	123	0	1.5	3	1	6	0
46	1	4	140	234	0	0	159	0	2.2	2	0	3	1
55	0	3	145	256	0	1	148	1	2.6	2	0	1	1
62	0	2	123	232	0	1	154	1	3.2	2	0	7	0
71	1	3	157	259	1	2	124	0	3.1	1	0	6	0

Table 3 | Community health care integration data set assignment table

Data description	Data type	Value range
Age	Integer	48–78
Sex	Binary number type	1 = male; 0 = female
CP	Integer	Disease symptoms and needs of the elderly floating population
Resting blood pressure	Real	95–200
Plasma steroid content	Real	125–265
Fasting blood glucose > 120 mg/d [bs]	Binary number	0 = No, 1 = Yes
Maximum heart rate	Real	0 = normal, 1 = abnormal, 2 = obvious left ventricular hypertrophy
Exercise angina	Binary number	0 = None, 1 = Yes
Motion induced drop	Real	0–6
Slope of ECG at maximum exercise volume (slope)	Integer	1 = up, 2 = flat, 3 = down
Number of main blood vessels (ca) measured by fluorescent staining method	Real	0,1,2,3
Prevalence of blood diseases of thalassemia	Integer	3,6,7
Sickness	Integer	0 = does not exist, 1 = exists

coefficients after forming the reference series is shown in Equation (9):

$$\zeta_i(k) = \frac{\min_i|x_o(k) - x_i'(k)| + \rho \cdot \max_i \max_k |x_o(k) - x_i(k)|}{|x_o'(k) - x_i'(k)| + \rho \cdot \max_i \max_k |x_o'(k) - x_i'(k)|} \tag{9}$$

Finally, based on the correlation coefficient ranking of each indicator, the analysis results were obtained, and the results of gray correlation analysis are shown in Figure 9, where the numbers and influencing factors in the correlation analysis results are shown in Table 4, and the correlation factor ranking is sorted by Table 5:

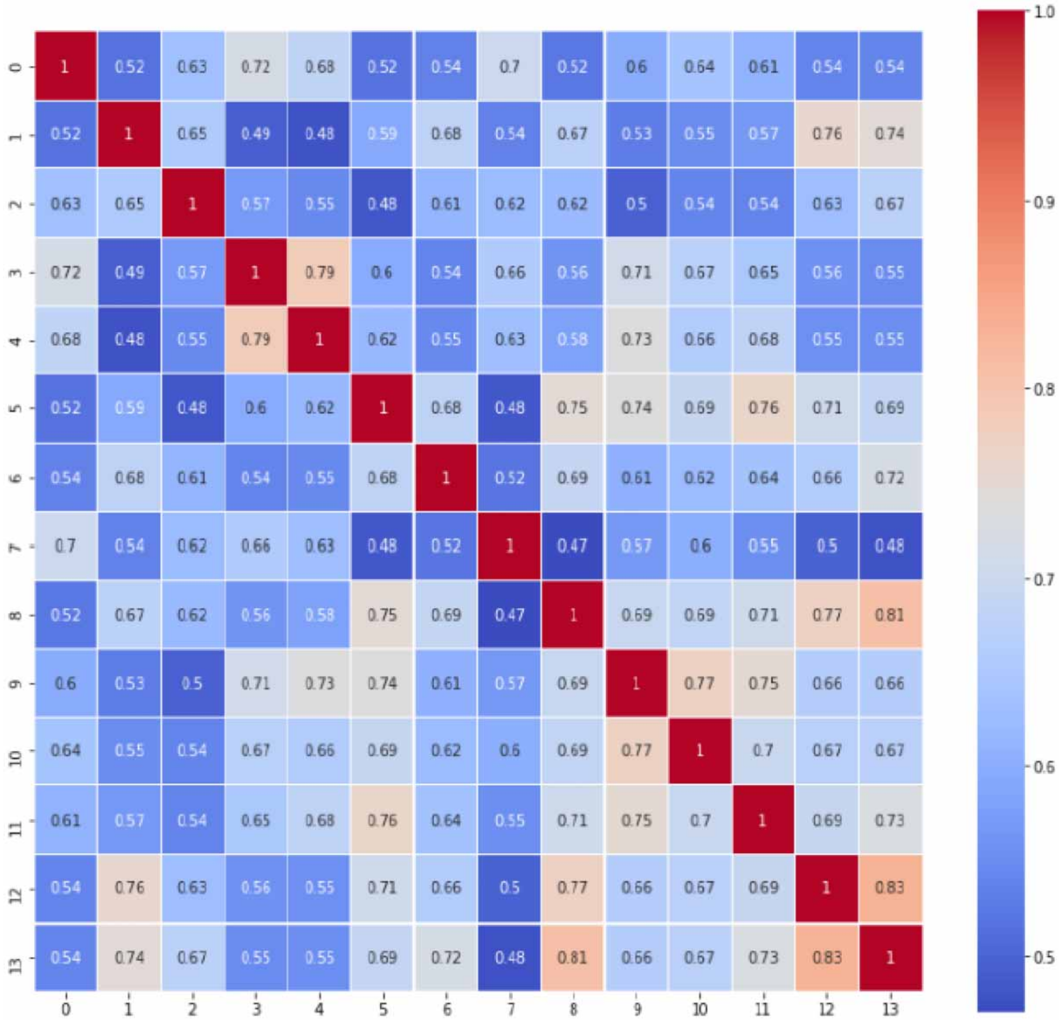

Figure 9 | Grey correlation fit of different indicators.

5. CASE STUDY

5.1. Model reliability and validity analysis

Based on the analysis of the data set module, the parameters were run 218 and 250 times in the two surveys, and 214 and 244 valid parameters were recovered for each, with a parameter efficiency of 98.17 and 97.60%, respectively. The general information of the elderly in both groups is shown in Table 6.

Therefore, we can obtain the results of the integrated numerical model of elderly floating population community medical care, as shown in Table 7.

On this basis, the ROC curve is drawn by comparing the predicted disease results of the CART decision tree model with the actual results, and the area of the ROC curve is obtained according to the formula for finding the AUC value of the ROC curve in Chapter 3, as shown in Table 8, and the ROC curve is shown in Figure 10.

As shown in Figure 10 and Table 9, the AUC value of the ROC curve reached 0.964, which is close to 1, while the significance level of the model has a P value less than 0.05, its KMO value is 0.93, the Bartlett's spherical test reaches a significant level, and there is no multiple loading, and the loading values of each entry on the corresponding factors are 0.478–0.897 indicates that the model classification effect is more satisfactory and has statistical significance.

In addition, in the test of the optimization-seeking algorithm, the division ratio of the training set to the test set is 7:3, and the learning curve of max_depth, for example, is shown in Figure 11. testscore changes with the increase of max_depth, and

Table 4 | Comparison table of sequence numbers of influencing factors

Influence factor	Corresponding serial number
Age	0
Sex	1
Types of chest pain	2
Resting blood pressure	3
Plasma steroid content	4
Fasting blood glucose > 120 mg/dL	5
Results of fine breath ECG	6
Maximum heart rate	7
Exercise angina	8
ST decrease caused by movement	9
The maximum exercise volume is the slope of ECG ST	10
Number of main blood vessels measured by fluorescent staining	11
Thal	12
Sickness	13

Table 5 | Ranking of impact factor correlations

THAL (12)	0.82
Exercise angina (8)	0.83
Gender (1)	0.72
Number of main blood vessels measured by fluorescent staining (11)	0.71
Results of resting electrocardiogram (6)	0.72
Fasting blood glucose > 120 mg/d (5)	0.75
Maximum exercise is the slope of ECG T (2)	0.68
Types of chest pain (10)	0.66
ST decrease caused by movement (9)	0.65

Table 6 | Comparison table of operating parameters of data sets

	Elderly living in Elderly Care Department ($n = 214$)		Elderly at home ($n = 244$)			
Project	Number of cases (n)	%	Number of cases (n)	%	x^2	P
Age						
60–65	16	7.28	29	11.56	7.403	0.115
66–70	32	15.52	48	18.21		
71–75	34	14.52	49	19.56		
76–80	34	15.98	36	13.52		
≥80	99	46.58	88	38.52		
Gender						
Male	75	34.55	105	42.63	3.125	0.078
Female sex	141	65.32	140	52.78		

Table 7 | Results of the univariate analysis of the numerical model of community health care integration for the elderly mobile population

	Elderly living in elderly care department ($n = 214$)				
Project	**Number of cases**	**%**	**Score**	***F/T* value**	***P*-value**
Age (years)				4.182	0.003
60–65	16	7.28	3.62 ± 0.22		
66–70	32	15.52	3.51 ± 0.32		
71–75	34	14.52	3.54 ± 0.31		
76–80	34	15.98	3.58 ± 0.28		
≥80	99	46.58	3.75 ± 0.25		
Spouse	142	66.8	4.31 ± 0.44	2.55	0.012
No spouse	70	33.24	4.15 ± 0.23		
Didn't go to school	23	10.25	4.1 ± 0.55	3.825	0.002
Primary school	105	49.56	4.11 ± 0.46		
Junior high school or technical school	66	30.25	4.11 ± 0.55		
High school or technical secondary school	15	6.55	4.5 ± 0.62		
Junior college	5	1.88	3.56 ± 0.22		
Bachelor degree or above	3	1.56	4.25 ± 0.25		

Table 8 | Decision tree curve parameters of the digital model of community health care integration for the elderly mobile population

				Progressive 95% confidence interval	
Inspection results	**The measure of area**	**Standard error**	**Progressive Sig**	**lower limit**	**Upper limit**
CART Decision Tree	0.955	0.016	0.001	0.958	0.988

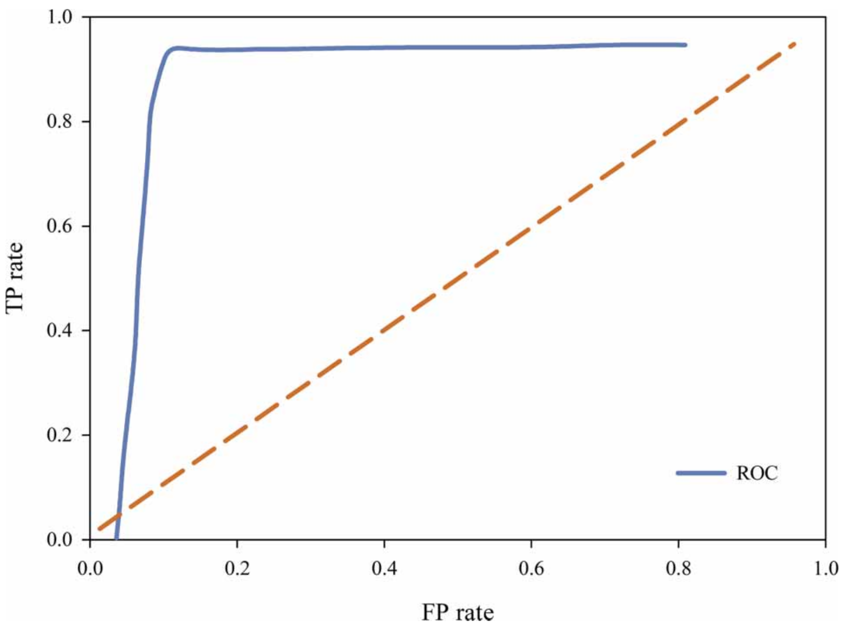

Figure 10 | Fitting curve of community health care integration for elderly mobile population.

Table 9 | Analysis of predicted load values of the community health care integration numerical model for mobile population

Actual classification	1 – Training set prediction classification		Total	2 – Test set prediction classification		Total
	Not sick	Be ill		Not sick	Be ill	
Not sick	325	4	329	136	4	140
Be ill	19	254	275	8	111	119
Total	344	259	604	144	115	259

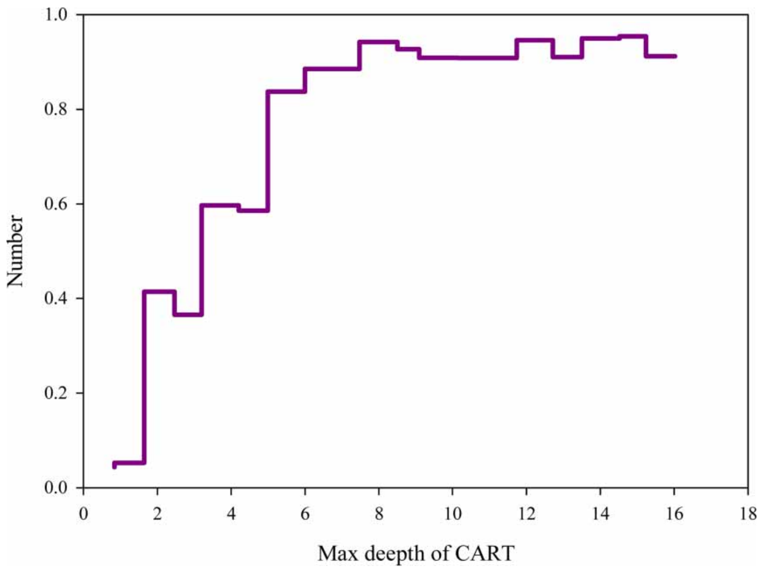

Figure 11 | Optimization results of the algorithm of the digital model of community health care integration for the elderly mobile population.

the model is best when max_depth is equal to 10. At this time the model has the phenomenon of overfitting, which decreases the classification accuracy and also decreases the computing efficiency, so the model works best when the max_depth parameter is 10. On this basis, we set maxdepth = 10 and obtain the optimal values of min_samples_leaf = 1 and min_samples_split = 3 by searching the grid and cross-validating the remaining two parameters in turn.

In summary, the CART decision tree classification algorithm constructed in this paper is implemented by running in a python 3.6 environment and compiled by jupyternotebook, firstly, the existing sample set is randomly partitioned into two parts, respectively, followed by cross-validation folding 10 times to build the model and improve the model robustness, as measured by experimental The accuracy and validity of the model were improved by 7% compared with the traditional model.

5.2. Empirical analysis

The statistical results showed that the selected data set, processed by the platform of community health care integration system for elderly mobile population, included 500 patients over 60–65 years old and 120 patients over 65 years old, accounting for 43.17% and 8.99% of the total sample, respectively. In the disease data (target > =1) there were 324 male patients and 70 female samples. As shown in Figure 12, the horizontal coordinates indicate the age of patients, the vertical coordinates indicate the number of sickness, and different colors represent sickness or not, it is easy to see that the number of people who do not suffer from heart disease decreases with age, the number of sick people shows an insignificant increasing trend, the number of people who are not sick shows an obvious decreasing trend with age, while the number of sick people reaches its peak between 55 and 67 years old, and the overall increasing The overall trend is increasing, this paper plotted the trend of the number of patients with age in the case data, using age as the horizontal coordinate and the percentage of patients with the disease as the vertical coordinate. As shown in Figure 12, the trend of the age distribution of the affected population shows that the pre-processed prevalence rate and the non-prevalence rate are normally distributed, and the affected population is mainly concentrated between 55 and 65 years old.

Further, in this paper, the statistical graph of the probability of disease by age was drawn based on the case information, and as shown in Figure 13, the probability of heart disease did not show an increasing trend with age. Taken together, the incidence of heart disease is not simply linearly related to age but is more influenced by various physical indicators that change with age. It can be seen that heart attack is caused by a variety of complex factors, therefore, in this paper, we will analyze and screen 13 categories of influencing indicators in the following.

It is not difficult to see that the learning ability of the optimized model algorithm is stronger, as shown in Figure 14 and Table 10. The significance level of its P value is less than 0.05, which indicates that the model has statistical significance for the prediction results of the elderly floating population in the community.

The smaller the value of the subsample parameter, the more conservative the algorithm will be, and therefore the smaller the probability of overfitting. colsample_bytree indicates the number of indicators of heart disease cases randomly used in the analysis of the health status of the mobile elderly population in community health care integration by a single decision tree. The higher the value is, the more likely to cause overfitting. The range of both parameters is set to 0.1–0.8, and the optimization is performed in steps of 0.01. After the above operation, the optimal values of the optimal parameters of XGBoost were obtained as n_estimators = 250, and the importance of the indicators of community health care integration for the elderly mobile population proposed by the model was assigned 4.48–5.00, with a full score of 52.17–100%; the importance of secondary indicators is assigned 4.43–5.00 with a full score of 47.83–100%; the importance of tertiary indicators is assigned 3.87–5.00 with a full score of 21.74–100%, and the confusion matrix is shown in Figure 15.

From the analysis results, the Stacking algorithm with the combination of multiple strong learners has significantly improved the accuracy of predicting the morbidity of the elderly mobile population in the community compared with other integrated algorithms and single algorithms, indicating that the Stacking algorithm can effectively combine the advantages of multiple strong learners, and the method of obtaining the predicted values through cross-validation can enhance the classification while avoiding overfitting. In terms of sensitivity and specificity and Jorden's index, the values of sensitivity and specificity of the Stacking algorithm are higher and similar compared with other algorithms, indicating that the prediction ability of onset of illness and non-illness of mobile elders in the community is stronger and more stable, and the classification

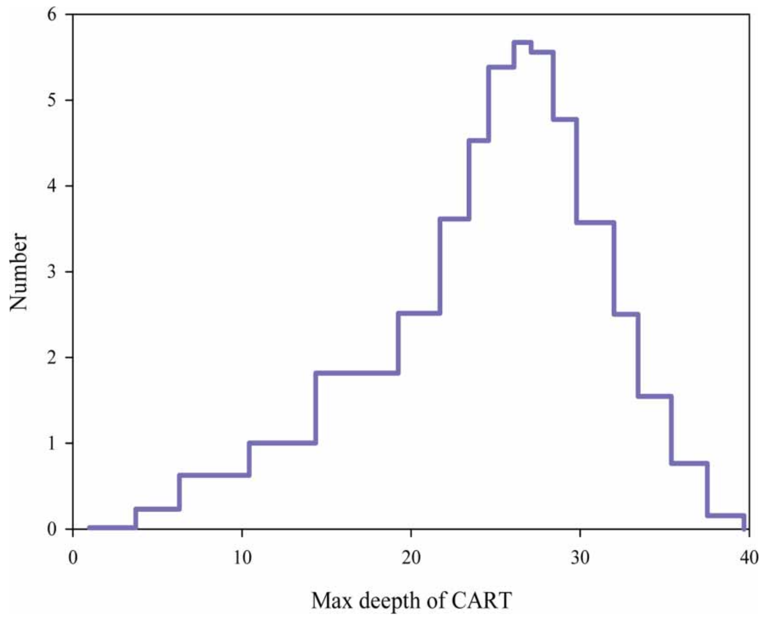

Figure 12 | Statistical chart of the distribution of the number of patients in the community health care integration model with age as a reference.

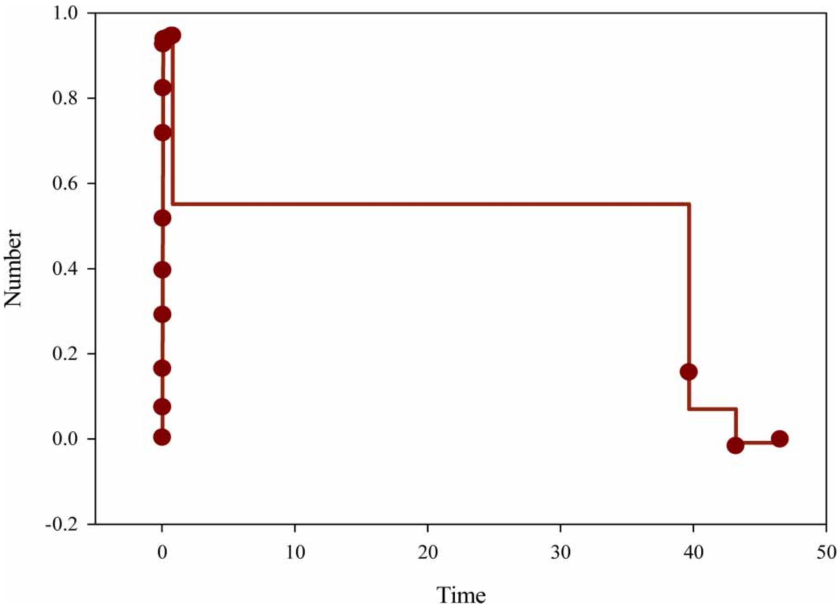

Figure 13 | Predicted medical resource occupancy results of the community health care integration model with age as a reference.

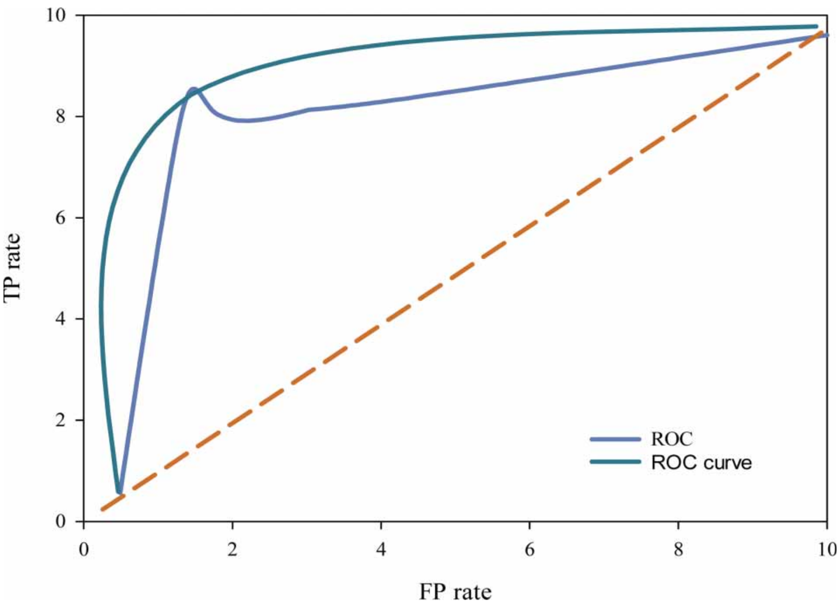

Figure 14 | Numerical model ROC optimization curve of community health care integration for elderly mobile population.

Table 10 | Comparison of area under the curve, standard error and significance level of kernel function model

				Progressive 95% confidence interval	
Inspection results	**The measure of area**	**Standard error**	**Progressive Sig**	**lower limit**	**Upper limit**
SVM Classification	0.945	0.018	0.001	0.941	0.987
SVM classification of polynomial kernel functions	0.952	0.015	0.001	0.918	0.985

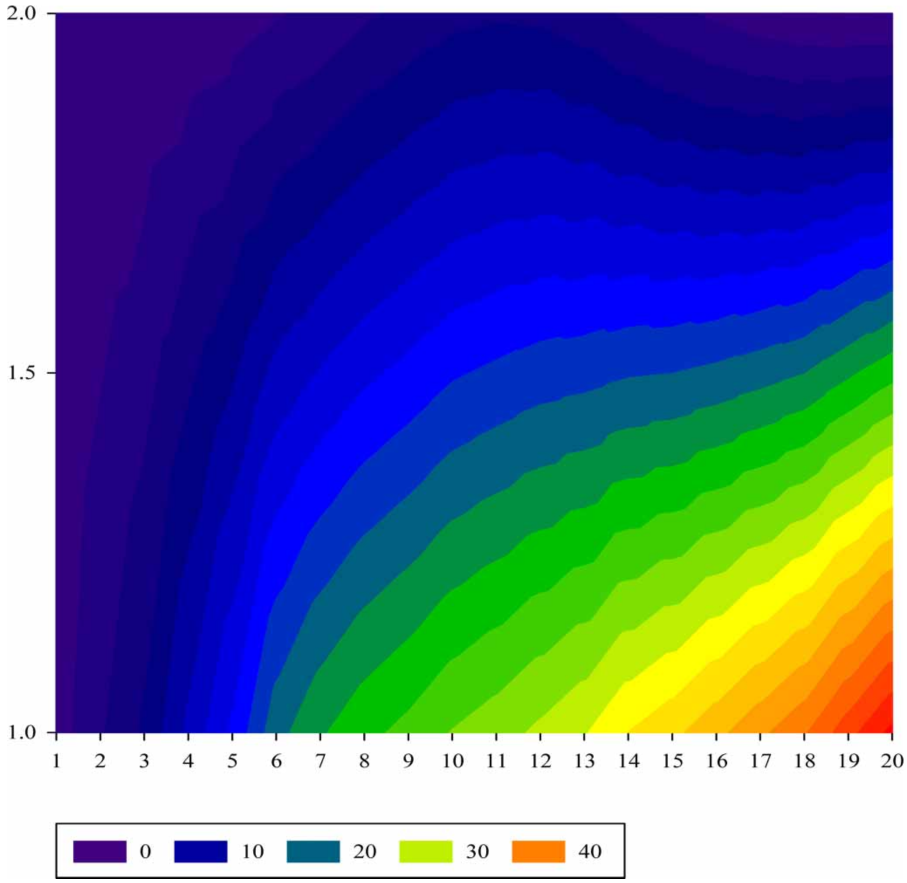

Figure 15 | Confusion matrix for predicting the elderly mobile population in the community.

effect is the best, and the learning ability of optimized single classifier is the best, which can enhance the match between predicted and actual classification and maximize the improve the classification performance.

6. CONCLUSION

In recent years, China's aging population has faced increasingly severe challenges due to rapid economic and social development, as well as the combined impact of fertility policies resulting in a significant decline in birth rates and delayed average life expectancy. Consequently, ensuring a high-quality life for the elderly has become an important issue for the Chinese government. In response to this, community medical care services have emerged as an effective means to alleviate pension problems and promote healthy aging. This study aims to construct a monitoring environment based on data analysis and intelligent coordination. It clarifies the utilization of Internet of Things devices and data collection methods, designs an E-R database model, defines a database storage model, calculates the significance of integrating community health care indicators for elderly migrant populations, conducts reliability analysis and empirical validity tests on the digital model of community medical integration for elderly migrants. The experimental results demonstrate that the KMO value of the model is 0.93 with Bartlett's sphericity test reaching statistical significance while avoiding multicollinearity issues. Each item loads between 0.478–0.897 onto its corresponding factor indicating higher accuracy (7% improvement) and effectiveness compared to traditional models. The establishment of this integrated health care-nursing care model provides valuable data references towards building an elder-friendly society in China.

FUNDING

The study was supported by the Major Humanities and Social Sciences Research Projects in Zhejiang higher education institutions, Grant Number:2021QN022.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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First received 23 January 2024; accepted in revised form 3 February 2024. Available online 23 February 2024